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A review on the forecasting of wind speed and generated power

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Abstract

In the world, wind power is rapidly becoming a generation technology of significance. Unpredictability and variability of wind power generation is one of the fundamental difficulties faced by power system operators. Good forecasting tools are urgent needed under the relevant issues associated with the integration of wind energy into the power system. This paper gives a bibliographical survey on the general background of research and developments in the fields of wind speed and wind power forecasting. Based on the assessment of wind power forecasting models, further direction for additional research and application is proposed.

Keywords: Forecasting; Wind speed; Wind power generation; Physical models; Statistic models; Spatial correlation models; Artificial intelligence

Contents

1. Introduction . . . 915
2. Forecasting models . . . 916
   2.1. Model input . . . 916
   2.2. Physical models . . . 916
   2.3. Conventional statistical models . . . 917
   2.4. Spatial correlation models . . . 917
   2.5. Artificial intelligence and new models . . . 918
3. Discussions and prospects . . . 919
4. Conclusion . . . 919
   Acknowledgement . . . 919
   References . . . 919

1. Introduction

With the deterioration of the environment and depletion of conventional resources, renewable energy has attracted people's attention. As a kind of non-pollution renewable energy, wind power has been growing rapidly in many areas, especially in Europe countries. For example in Spain, wind power generation account for 4% of its electricity consumption [1].

Wind power generation depends on wind speed. Wind speed could be easily influenced by obstacle and terrain. It also varies with height, so the random character of wind is significant. The reliability of wind power is not satisfactory because it cannot supply steady electricity to power system. So when the wind power penetration (i.e. proportion of wind power in a power system) grows, the power system operation will be affected [2]. As a result, the power system regulators must make detailed schedule plans and set reserve capacity for it. To reduce the reserve capacity and increase the wind power penetration, the accurate forecasting of wind speed is needed.

To handle wind speed prediction, many methods have been developed. These methods can be divided into two categories.

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The first is the physical method, which use a lot of physical considerations to reach the best prediction precision. The second is the statistical method, like ARMA model, which aims at finding the relationship of the on-line measured power data [3]. Physical method has advantages in long-term prediction while statistical method does well in short-term prediction. However, this classification is not absolute. Few practical forecasting uses physical or statistical method only. Both physical and statistical models are utilized simultaneously in typical forecasting method. In which, to train the system on the local conditions, NWP results are regarded as input variables together with historical data and statistical theories. In the recent years, some new methods are catching researcher's attention. New methods based on artificial intelligence like artificial neural network (ANN) and fuzzy logic models are widely used [4]. Also, hybrid models, which come out nowadays, of cause are advanced ones and have less error than others.

Wind power generated by wind turbines has intimate relationship with wind speed. Wind speed is converted into power through characteristic curve of a wind turbine. And the forecasting of wind speed and wind power has the same principle. Thus wind speed and wind power are reviewed together and the emphasis is the forecasting method or model. The forecasting method is not classified conventionally as physical and statistical, for most of methods include both of them. This paper divides the forecasting methods into four categories: the physical model, the conventional statistical model, the spatial correlation model, and the artificial intelligence and other new methods.

This paper is organized as follows. Section 2 presents model input and describes various kinds of forecasting models in detail. In Section 3, these forecasting models are compared and evaluated. Finally, Section 4 presents the main conclusion of the paper.

2. Forecasting models

2.1. Model input

Choosing appropriate input variables is important to build an efficient forecasting model. Different variables are needed for different models.

For a physical model, it uses physical considerations to predict the future speed and direction of wind, so the input variables will be the physical or meteorology information, such as description of orography, roughness, obstacles, meteo and so on [5].

For a statistical model, the historical data of the wind farm may be used, and NWP output is mostly used as input. Thus the physical method serve as an initial analysis, and its results make the statistical method more efficient. This is not always the case. The historical wind speeds of the same site as well as the neighboring sites are needed in spatial correlation model, and the power curve of wind turbines is also needed for the forecasting of wind power [6].

2.2. Physical models

Physical models use physical considerations like terrain, obstacle, pressure, and temperature to estimate the future wind speed. Sometimes they are only the first step to forecast the wind, which is supplied as auxiliary input of other statistical models. NWP model is developed by meteorologists for large-scale area weather prediction. The model does not have accurate results in short-term prediction. In order to achieve better results, NWP model solves conservation equations numerically at the given site. In the same time, to represent the topography, digital elevation models must be utilized in NWP model so as to reach more accurate results [9]. In the end, model output statistics (MOS) should be used to reduce the remaining error. The developments in this field are listed as follows.

An automatic on-line prediction system for wind farm production output is described by Landberg [5], and the NWP model is utilized (in this article it was HIRLAM model). As it was large-scale forecasting, when zoomed in to one site, the detailed data was supplied by WAsP program, which took effect of obstacles, roughness into account. Then PARK program is used to deal with the shadowing effects of turbines. In the end, the MOS models were used. The model results are compared with the persistence model and a conclusion is given that the prediction model performed better than the persistence model after 6 h, and the mean absolute error of the prediction model is about 15% of the installed capacity [8].

Negnevitsky et al. pointed out that the NWP model should apply accurate digital elevation models (DEMs) and model output statistics (MOS) corrections for short-term prediction, although they did not perform well in very short-time frame [10].

El-Fouly et al. summarized that physical models were developed based on weather data. The models took many physical considerations including shelter from obstacles, local surface roughness, orography effect, speed up or down, etc. These models dealt with the prediction for 0–48 h ahead [11].

Landberg and Watson developed the research on eight different models including NWP model (such as HIRLAM and the UK MESO model), neural network model and so on. They compared the results of the eight models with persistence model and concluded that these models all outperformed the persistence model. At sites with high mean wind speeds, the neural HIRLAM/WAsP model did extremely well. However, considering the prediction horizon is of 3–6 h, the persistence model should be used because of its good performance in very short-time prediction. The neural networks method which was studied by authors did not show any outstanding performance, mainly because the persistence model performs quite well in short-term prediction [12].

Giebel et al. published a review on the art of short-term prediction. They introduced the numerical weather prediction-based models comprehensively. In the study, most of the studies in this field are listed, and the application of the models no longer in action and the models currently in use is summarized [7]. Short-term hydroscheduling problem is categorized as a class of large-scale, discrete, nonlinear, and non-convex

problem [14]. Therefore, it is crucial to have a more accurate model representing the hydraulic system for obtaining a reasonable schedule to guide the hydro producer operations, e.g. minimum-up/minimum-down time limits are taken into account.

2.3. Conventional statistical models

Conventional statistical models are identical to the direct random time-series model. Based on a number of historical data, pattern identification, parameter estimation, model checking are utilized to make a mathematical model of the problem. According to the methods which is proposed by Jenkins, these models can be divided as follows: autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), auto regressive integrated moving average model (ARIMA) [13].

The random time-series can be described as follows:

$$x_t = \sum_{i=1}^{n} \varphi_i x_{t-i} + \alpha_t - \sum_{j=1}^{m} \theta_j \alpha_{t-j}$$

where φ_i is the autoregressive parameter, θ_j is the moving average parameter, α_t is the normal white noise, x_t is the value of wind speed at time t [14].

This is a typical ARMA model, and if m is assumed to be zero, it will represent AR model. Persistence model introduced in Section 3 is the simplest ARMA model which applies the present value as the value of any time ahead. If we apply ordered differential transformation to the model, ARIMA model can be obtained.

Another statistical method is Kalman filters model. It takes wind speed as state variable and establishes state-space models, and the Kalman filters algorithm is used to predict the future wind speed. It is suitable for online forecasting of wind speed [15].

Ding et al. presented a wind speed forecast model based on time-series analysis method. In order to check the effectiveness of the employed model, An Information Criterion (AIC) function is used. According to the AIC value of the models, ARMA (5, 4) is employed to calculate the 1-month average wind speed and the 1 h averaged wind speed, and the results are compared with the actual wind speed. In the end, the effectiveness of wind speed forecasting is concluded [15].

Lalarukh and Yasmin used a kind of time-series models considered autocorrelation, non-Gaussian distribution and diurnal nonstationarity. An ARMA model is used based on the wind speed data of 2 years. The conclusion was that forecast values of variance and wind speed with a confidence interval of 95% can be acceptable both for short- and long-term prediction [16].

To forecast the wind speed of the South Coast of Oaxaca, both ARIMA model and ANN model were used and compared to each other by Erasmo and Wilfrido. The final results indicated that the seasonal ARIMA model presented a better sensitivity to the prediction of wind speed. However, when the number of training vectors is increased for the ANN model, its performance would be improved [17].

Torres et al. used the ARMA model to predict the hourly averaged wind speed and compared it with the persistence model. In their study, the transformation and standardization of the time-series is proved very important to form the appropriate model. If the RMSE is not to surpass the 1.5 m/s limits, the method proposed in the article is only applicable to short-term prediction. They also concluded that the ARMA model outperformed the persistence model. For forecasting horizon of 1 h, the persistence had less errors than ARMA model, while for forecasts 10 h in advance, the errors of ARMA model are between 12% and 20% smaller than of persistence model [18].

Costa el al. applied Kalman filters to predict wind speed and compared the performance with persistence. And a conclusion was given that the persistence performed better for hourly data, and the prediction model did best for 5 min time step [19].

2.4. Spatial correlation models

Being different with other models, the spatial correlation models take the spatial relationship of different sites' wind speed into account. The wind speed time-series of the predicted points and its neighboring sites are employed to predict the wind speed [2]. This kind of model is more difficult than the typical time-series models because the measurement of many spatial correlated sites' wind speed values and timely transmission are all needed. Recently, many researches have been done on spatial correlation models.

In [20], Damousis et al. proposed a model combining the fuzzy method and spatial correlation together. The model utilized the data measured at neighboring sites with a radius up to 30 km, and the training method is a genetic-based algorithm. The model was applied both over a flat terrain and complex terrain. In the end, it was found that the data from the remote sites did improve the forecasting accuracy over the flat terrain, but while over the complex terrain, it even made the forecast worse. The spatial correlation did not reach a good effect.

In [6], Alexiadis et al. proposed a spatial correlation predictor (SCP) based on measured data of another site. More than 7 years' data of six sites was used to test the model, and it performed well.

The reduction of the prediction error by using spatial correlation model was studied by Focken et al. [21]. The error of a single site was compared with an ensemble of wind farms, and it was found that the error of spatial correlation model was less than that of a single site because of the spatial smoothing effect. The error reduction was mainly decided by the size of the region and the number of sites it contained. Finally a saturation level was found, which had the meaning that only few sites were sufficient to determine the improvement of the power production.

In [22], Barbounis and Theocharis presented a locally feedback dynamic fuzzy neural network (LF-DFNN) for wind speed forecasting using spatial correlation model. In the study, two remote sites were chosen with the base site so that the three sites were lined along the direction of the prevailing winds. The pressure gradients, the heat transfer, the terrain landscape and three cases of time delay were considered. In the end, it was

proved that the proposed model outperformed other network models.

Another spatial correlation-based neural network was further developed in 2007. Although it was proved better than other static neural and neuro-fuzzy models, its performance did not surpass the LF-DFNN model mentioned above. The reason was that the former LF-DFNN model employed wind direction while not the latter [23].

A model based on the ANN method and spatial correlation was developed by Bilgili et al. [24]. The mean monthly wind speeds of reference stations were used to predict the target stations' wind speed. The prediction results were compared with actual data, and it was found that the maximum MAE was 14.13% while the minimum was 4.49%. It was finally concluded that the ANN method based on wind speed of reference stations could predict the wind speed of target stations without any topographic details or other meteorological data.

2.5. Artificial intelligence and new models

Recently, with the development of artificial technique and other forecasting methods, various new models for wind speed and power prediction are mushrooming. The new developed methods include ANN, fuzzy logic methods, support vector machine, and some hybrid methods.

ANN is one of the most widely used models in the last decade, which consists of many layers, an input layer, an output layer and one or more hidden layers. There are a lot of neurons in each layer, which were connected to neurons of the previous layers while the neurons in the same layer are independent with each other. Each connection has its own weight, and each neuron has a transfer function (in the hidden layer it usually is sigmoid function) [6]. The training process is the procedure to obtain the weights of each connection and the neurons threshold value [25]. Some training algorithms were developed, including the back-propagation (BP) algorithm, the Levenberg Marquardt (LM) algorithm and so on [14]. Their aim was to achieve the minimal value of network error.

Another model is the fuzzy logic model, it utilizes membership values in the interval [0, 1] and the fuzzy variables like long, medium and short, to explain the membership. It is used where a system is difficult to model exactly [20]. Support vector machine is a novel approach which can overcome some disadvantages of neural network, such as local minimal point, over learning, etc. [26].

A research was developed on ANN and the results were compared with the AR model by Mohandes et al. [27]. The ANN model had been widely used because of its excellent ability in its learning from experience. The mean of monthly and daily wind speed prediction were tested based on the root mean square errors. The result indicated that the ANN was superior to the AR model, and outperformed the AR model in multi-step prediction. The computational complexity of AR compared with ANN could be neglected by using advancing computers.

In [28], Sfetsos presented a novel approach based on ANN model and time-series of target station. Ten minutes' data was used to do multi-step forecasting, and the average results were used to generate the mean hourly predictions. The model was tested on two independent data sets. It produced root mean square errors about four times lower than other models which were based on mean hourly data.

In [29], Flores et al. supplied a control algorithm for wind speed and active power prediction. The algorithm was based on ANN model using back-propagation method. Two different types of data sets were used to test the algorithm. The conclusion was that this kind of model could help the producers and utilities to obtain the maximum economic benefits.

In [30], wind speed, relative humidity and generation hours were used as input variables to train an ANN-based network by Carolin Mabel and Fernandez. The prediction results were compared with actual data and the performance was found good. The similar work was done by Xiao et al. using a back-propagation network [31].

In [32], Li put forward a method called the recurrent multilayer perception neural networks (RMLP) to predict power generation. The Kalman filter based back-propagation algorithm was used to train the network. It was found that the prediction model performed better in long-term prediction than in short-term prediction, and the wind power time-series could also affect the performance. Additionally, the author concluded that this model could be used to predict the practical highly changing wind power generation. Barbounis and Theocharis also developed a neural network model, the recurrent neural networks for long-term prediction. Their training method was a class of optimal on-line learning algorithms. The results provided that the recurrent neural networks outperformed the atmospheric and time-series models [33].

Riahy and Abedi put forward a novel method based on the linear prediction method. The performance of this model could be improved by increasing the model order, but it could decrease the stability of the system. A filtering method was used to filter out the undesired parts of frequency components of wind speed. Compared with the actual wind speed data, it was proved to be an efficient method to predict wind speed [34].

Damousis et al. proposed a fuzzy model based on spatial correlation method to predict wind speed and power generation. It provided good performance over flat terrain, while in the complex terrain, the performance was deteriorated [20]. Another fuzzy method was developed by Sideratos and Hatziargyriou. They combined the fuzzy model with neural networks and obtained satisfactory results [35].

Researchers have studied in many other new prediction methods. An AR model based on Bayesian approach was utilized by Miranda and Dunn. It was proved to be an effective method due to the flexibility of Bayesian approach in model development [36]. Mohandes et al. introduced the support vector machines (SVM) for wind speed prediction and compared it with the multilayer perceptron neural networks. The results proved that the SVM model had less root mean square errors than MLP model [37]. Ji et al. did further research on SVM. A support vector classifier was utilized to estimate the forecasting error and lower mean square error

and mean absolute percentage error than traditional SVM method were obtained [26].

3. Discussions and prospects

Forecasting models reviewed above have their own characteristics, and they can perform well in different situations. NWP models are good at predicting large-scale area wind speed and can achieve better results in long-term forecasting. Often they were used as input of time-series models as ARMA, ANN, etc., and help them to obtain better results. The persistence models are considered as the simplest time-series models. They can surpass many other models in very short-term prediction. In spite of the unstable forecasting efficiency, they have been widely used in practice. Scholars did most research on time-series based models during the past 30 years. This kind of forecasting models such as Box.Jenkins models (i.e. AR, ARMA models, etc.), neural network-based models and fuzzy logic models use large number of historical data for modeling input and can achieve accurate results in short-term prediction. Neural network models and fuzzy logic models are new developed artificial intelligence based models. Neural networks perform well for raw data input and have strong learning and training abilities. Fuzzy logic models outperform others when dealing with reasoning problems, while the learning and adjusting abilities are mediocre. New methods combined the fuzzy logic and neural networks together and created excellent performance. The accurate comparison of all the methods is quite difficult because these methods depend on different situations, and the data collection is a formidable task. However, there are some comparison and the approximate results, which proved that the artificial-based models outperformed others in short-term prediction.

From the development of wind speed and power prediction we can see the trend approximately. The prospects are as follows:

Deepen further study on artificial intelligence methods and improve their training algorithm aiming at more accurate results.
Combine different physical and statistical models to achieve good results both in long- and short-term prediction.
Deepen further research on the practical application of the models, not only in theoretical.
Put forward new mathematical methods.

4. Conclusion

This paper presents a review on the forecasting of wind speed and generated power. Various forecasting models are introduced and a lot of researches on the models are presented. The models all have their own characteristics. Some of them are good at short-term prediction while others perform better in long-term prediction; some are simple and widely used while other complex ones have more accurate results. Recently, with the development of artificial intelligence and mathematical technique, a lot of new methods were put forward. Many of them are more excellent than the conventional methods and have good development prospect. Based on the development history of wind speed and generated power prediction, the possible trend is proposed in the end.

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